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The effect of day-to-day temperature variability on agricultural productivity

Zhixiao Zou[1,2], Chaohui Li[3,4], Xudong Wu[5,4,*], Zheng Meng[6] and Changxiu Cheng[1,2,*]

[1] Key Laboratory of Environmental Change and Natural Disaster, Beijing Normal University, Beijing 100875, People's Republic of China
[2] State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing 100875, People's Republic of China
[3] Laboratory of Systems Ecology and Sustainability Science, College of Engineering, Peking University, Beijing 100871, People's Republic of China
[4] Potsdam Institute for Climate Impact Research, Potsdam 14473, Germany
[5] School of Soil & Water Conservation, Beijing Forestry University, Beijing 100083, People's Republic of China
[6] School of management, China University of Mining and Technology (Beijing), Beijing, People's Republic of China
[*] Authors to whom any correspondence should be addressed.

E-mail: wuxudong@bjfu.edu.cn and chengcx@bnu.edu.cn

Keywords: agricultural productivity, climatic extremes, day-to-day temperature variability, rainfall pattern change, heterogeneous effects

Supplementary material for this article is available online

Abstract

With rising extreme weather events due to climate change, the impact on agricultural production has become increasingly severe. Yet, there has been a significant gap in research that assesses the influence of day-to-day temperature variability on agricultural productivity on a global scale. Our study addresses this gap by exploring the effects of day-to-day temperature variability and the change of rainfall patterns on agricultural productivity worldwide from 1961 to 2018. The results reveal that day-to-day temperature variability not only has a direct, negative impact on agricultural total factor productivity (TFP), but also influences it by modulating the effects of monthly average temperatures and wet days. One unit increase of day-to-day temperature variability leads to a 2% decrease in TFP. Day-to-day temperature variability neutralizes the impact of monthly average temperature on TFP, while exacerbating the impact of wet days on TFP. Furthermore, extreme rainfall events result in a consistent negative marginal effect across all countries/seasons/rainfall intervals. This study also identifies differentiated impacts across countries with varying income levels. Low-income regions' TFP demonstrates markedly significant sensitivities to both monthly average temperatures and daily temperature fluctuations, which means less resilient. Furthermore, the impacts of general and extreme rainfall are comparatively less pronounced in high-income countries, indicating higher resilience to climate variability in these regions and a relative vulnerability to extreme weather events in low-income regions. Our findings illuminate the intricate and multifaceted role that daily temperature variability plays in agricultural productivity, providing a theoretical basis for understanding the heterogeneous impacts of climate change on agriculture and contributing insights into the broader discourse on climate resilience and agricultural sustainability.

1. Introduction

The ongoing climate change has led to an increased occurrence of heat shock, intensified precipitation, and extreme weather events (IPCC 2014). Given the high sensitivity of agriculture to climatic variations, the heat stress and changing rainfall patterns pose significant threats to agricultural production (Lobell *et al* 2011, Vogel *et al* 2019), the disturbance of which may severely jeopardize global food security. Therefore, investigating the impacts of climate change on agricultural productivity is crucial for mitigating global hunger as well as fostering sustainable food production (Alston *et al* 2009, Federico 2010, Bocchiola *et al* 2019, Hasan *et al* 2020).

Agricultural total factor productivity (TFP) serves as an economic index for measuring the ratio of agricultural output (encompassing all crops and livestock commodities) by production inputs such as land, labor, and capital (Fuglie 2018). In comparison to other agricultural metrics such as aggregate agricultural output and crop yield, TFP reflects the efficiency of how agricultural economic activities transform the inputs into outputs, thus providing a more comprehensive representation of the economic efficiency of agricultural production (Ball *et al* 1997, Christiansen *et al* 2022). A higher agricultural TFP implies higher outputs from the same set of inputs (Fuglie 2021). Inherently, agricultural production is susceptible to stochastic fluctuations, which means that the agricultural TFP growth may oscillate around a medium value. Hence, the average growth rate of agricultural TFP measures the capacity to augment production in the long term without additional inputs. Since temperature and moisture are crucial external physical factors affecting crop and livestock growth, agricultural production is naturally linked to climate change (Gornall *et al* 2010). If climate change adversely affects agricultural production, this typically results in a slowdown in agricultural TFP growth. However, the correlation between agricultural TFP growth and climate variability is not fully understood. Therefore, it is important to understand the correlation between the growth rate of agricultural TFP and climate variability, which can shed light on the adaptability of agricultural production to changing climatic conditions (Ukhurebor and Aidonojie 2021, Ukhurebor *et al* 2022, Jiang *et al* 2023).

Previous studies that investigate the impact of climate change on agricultural TFP mainly focus on the variation in the annual mean value of climate variables (Liang *et al* 2017, Letta and Tol 2019, Ortiz-Bobea *et al* 2021). However, as demonstrated in existing studies (Lobell *et al* 2013, Teixeira *et al* 2013, Birthal and Hazrana 2019), productivity losses attributed to heat stress often occur on a daily scale, which means that annual average temperature is incapable of depicting the impact of daily temperature variations on agricultural TFP. Temperature variability can affect crop yields by altering the length of the growing season (Cabas *et al* 2010), such as delaying grain-filling (Wheeler *et al* 2000). Additionally, it also can reduce the maximum leaf area, thereby impacting photosynthesis and biomass accumulation (Riha *et al* 1996). Furthermore, increasing evidences suggest that climate variability has a significant influence on various agricultural outputs in terms of crop yields (Rowhani *et al* 2011, Luan *et al* 2021) and livestock productivity (Ortiz-Bobea *et al* 2018), as well as on agricultural inputs including labor productivity (Shi *et al* 2015, Yang *et al* 2018, Hovdahl 2022), irrigation decisions (Negri *et al* 2005), and energy investments (Khan *et al* 2021). Therefore, the cumulative impact of day-to-day temperature variability on these agricultural production elements may significantly influence agricultural TFP at a macroeconomic level. Additionally, as demonstrated by Kotz *et al* (2022), the overall agricultural output exhibits an evident response to variations in rainfall and higher-order moments of its distribution. Therefore, it is also imperative to take changes in rainfall patterns into account when investigating the impact of climate variations on agricultural TFP.

In this study, we took a preliminary effort to investigate the impact of day-to-day temperature variability on agricultural TFP. Firstly, we undertook a temporal-spatial aggregation of gridded meteorological data and NDVI (normalized difference vegetation index (NDVI) data to the national scale. Secondly, this study examined the impacts of climate variability on agricultural TFP, by giving consideration to both the individual effects as well as the combined effects resulting from the interactions between different independent variables on agricultural productivity. Specifically, we examined the variables including day-to-day temperature variability, average temperature, rainfall, extreme rainfall as well as their interactions at a national scale from 1961 to 2018. To identify the heterogeneity among countries with varying income levels, we constructed a set of regression models to differentiate the impact of climate change on agricultural productivity for high-income and middle-to-low-income nations. The results of this study may help establish a robust foundation for policy incentives towards safeguarding agricultural productivity and food security in nations with divergent economic levels.

2. Materials and methods

2.1. Economic data

In this study we obtained the international Agricultural TFP dataset from the United States Department of Agriculture (USDA) Economic Research Service (ERS). This dataset provides national-level TFP measures for 172 countries from 1961 to 2019 (For details see SI 1.1). However, because some crops have growing seasons that span calendar years, we included TFP data from 1962 to 2018 in our regression models.

2.2. Spatial-temporal aggregation of cropland and NDVI

To aggregate daily-scale climate variables from grid cells to the national level, a regionally-weighted approach is employed that spatially integrates

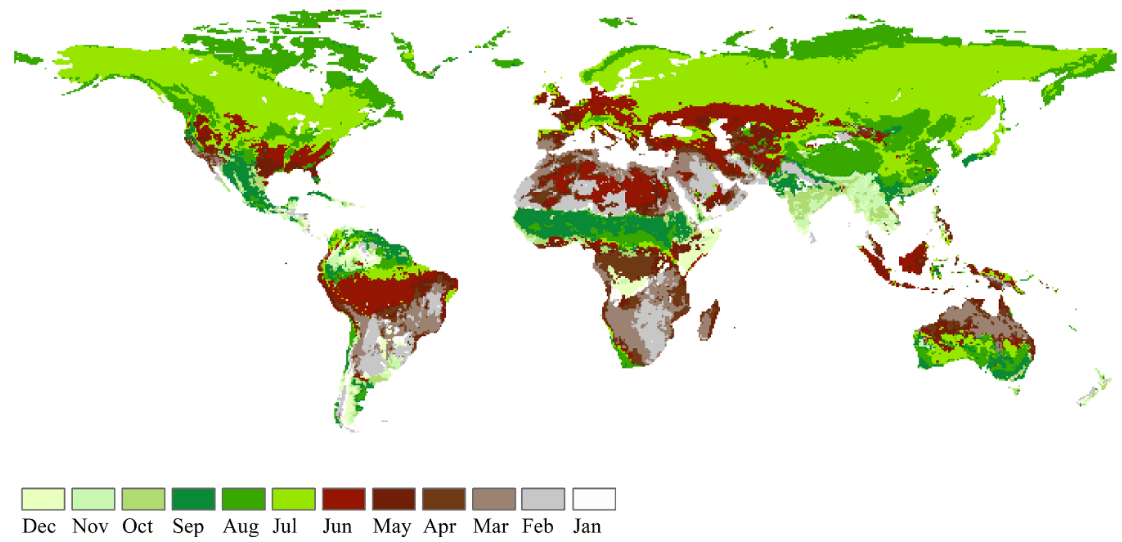

Figure 1. Month with highest value of NDVI: 'greenest month'.

grid-level data up to the national scale. The weighting factor $w_{r,x}$ for each grid cell is determined based on the proportion of cropland within that cell (supplementary figure 1). Here, r denotes the region, and x represents the grid cell. The grid-level land cover data is sourced from Ramankutty *et al* (2008).

The regression models are based on climate variables observed during the 'green season', which is defined as the three-month period centered around each grid's 'greenest month' according to the NDVI data (Eastman *et al* 2013, May *et al* 2020, Ortiz-Bobea *et al* 2021). The NDVI dataset used is the normalized difference vegetation index-3rd generation: NASA/GFSC GIMMS dataset for the years 1981–2015 (NCAR 2023). The month with the highest NDVI value in a given year determines the 'greenest month' for each grid cell (see figure 1). Climate variables are aggregated within the 'green season'. Crop rotation farming, such as the commonly observed wheat-corn rotation in Northern China, is not taken into account due to data unavailability. Additionally, since the NDVI data is at a raster scale, the 'green season' already excludes periods of the year with limited vegetation growth.

2.3. Climatic metrics

The meteorological data used in this study, such as daily surface temperature and total rainfall, were obtained from the 20CRv3-W5E5 dataset, which originated from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP). The 20CRv3-W5E5 dataset is an interpolation of W5E5 v2.0 (Lange *et al* 2022) and the Twentieth Century Reanalysis version 3 (20CRv3, Slivinski *et al* 2021), and has a spatial resolution of 0.5° (For details see SI 1.3).

Given that macroeconomic data are compiled at a yearly scale, it is essential to compute climate variables on an annual basis. Thus, day-to-day temperature variability is averaged within the 'green season' of a specific year to generate an annual measurement, which is performed in accordance with the spatial-temporal aggregation, as shown in equation (1):

$$\tilde{T}_{r,y} = \frac{1}{n}\sum_{m}^{n}\frac{1}{\sum_{x}^{N_r} w_{r,x}} \times \sum_{x}^{N_r} w_{r,x}\sqrt{\frac{1}{D_{m,y}}\sum_{d}^{D_{m,y}}\left(T_{x,d,y} - \bar{T}_{x,m,y}\right)^2} \quad (1)$$

where $\tilde{T}_{r,y}$ measures day-to-day temperature variability for country r in the year y. Here $T_{x,d,y}$ denotes the daily average temperature for grid x on day d in the year y, while $\bar{T}_{x,m,y}$ is the monthly average temperature for that grid in the given year. $D_{m,y}$ indicates the number of days in month m for year y; N_r is the number of grid cells that at least partially fall within the specified region r. The weight $w_{r,x}$ is the proportion of cropland according to land cover data for that grid cell. Given that the 'green season' spans three months, n is set to 3 (supplementary figure 2).

In our grid-based calculations, this study employs multiple metrics for daily rainfall. We define thresholds for wet days at 0.1, 1, and 90 mm d^{-1} according to a previous study (Kotz *et al* 2022). For extreme rainfall days, the thresholds are set at the 95th, 99th, and 99.9th percentiles of the historical (1979–2019) daily rainfall distribution at the grid scale (Barma *et al* 2022). The number of wet and extreme rainfall days, denoted as $RD(R_C)_{x,y}$, is calculated for each year y and for each specified threshold

R_C, which is illustrated in equation (2):

$$RD(R_C)_{x,y} = \sum_{m}^{n} \sum_{d}^{D_{m,y}} H(R_{x,d} - R_C) \quad (2)$$

H is the Heaviside step function, $H(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geqslant 0 \end{cases}$. Standardized monthly rainfall deviations for cell x, year y, denoted as $RM_{x,y}$, which are used to better account for intra-annual variability of weather conditions by looking at monthly values and comparing them to their long-term distribution (For details see SI 1.4), are shown as below:

$$RM_{x,y} = \sum_{m=1}^{n} \frac{R_{x,m,y} - \bar{R}_{x,m}}{\sigma_{x,m}} \frac{\bar{R}_{x,m}}{\overline{RA}_x} \quad (3)$$

where $R_{x,m,y}$ represents the total rainfall for cell x, year y, and month m; $\bar{R}_{x,m}$ denotes the historical mean rainfall for that particular cell x and month m, and $\sigma_{x,m}$ is the historical standard deviation of monthly rainfall totals in that cell and $\overline{RA}_x$ is the historical mean of rainfall totals during 'green season' in that cell. $RM_{x,y}$ is calculated by aggregating monthly rainfall deviation for cell x in year y. Since the 'green season' lasts for three months, n is set to 3.

2.4. Regression model and marginal effects

We applied a mixed-effects model to explore the effects of day-to-day temperature variability and the change of rainfall pattern on agricultural total factor productivity. To account for the interaction between temperature and rainfall, we included cross-terms involving temperature and rainfall-related variables. i.e. temperature- and rainfall-related variables multiplied together. Based on the bayesian information criterion (BIC) and adjusted R^2 (see table 1), we used the thresholds of 1 mm d^{-1} and the 95th percentile of historical values to identify wet days and extreme rainfall days. The production function, which incorporates the USDA's estimation of TFP (For details see SI 1.5), was used to examine the relationship between total output, total input, weather, and technology. The production function is expressed as $Y_{r,y} = e^{f(M_{r,y})} A_{r,y} X_{r,y}$, which could be transformed as $Y_{r,y}/X_{r,y} = e^{f(M_{r,y})} A_{r,y}$. $Y_{r,y}$ represents the total agricultural output in year y in region r; $A_{r,y}$ measures technological progress; $M_{r,y}$ is the impact of weather, and $X_{r,y}$ is the total agricultural input in year y in region r (For details see SI 1.5). Therefore, we constructed the regression model as below:

$$\begin{aligned} ln\mathrm{TFP}_{r,y} = {} & \alpha_1 \bar{T}_{r,y} + \alpha_2 \bar{T}_{r,y}^2 + \alpha_3 \tilde{T}_{r,y} + \alpha_4 \bar{T}_{r,y} * \tilde{T}_{r,y} \\ & + \alpha_5 R_{r,y} + \alpha_6 R_{r,y}^2 + \alpha_7 RM_{r,y} + \alpha_8 R\hat{D}_{r,y} \\ & + \alpha_9 RD_{r,y} + \alpha_{10} \tilde{T}_{r,y} * R\hat{D}_{r,y} + \mu_y \\ & + \gamma_r + \epsilon_{r,y} \end{aligned} \quad (4)$$

where $\mathrm{TFP}_{r,y}$ represents the TFP in region r during year y; $\bar{T}_{r,y}$ is the monthly average temperature during the 'green season' of each year, and $\tilde{T}_{r,y}$ denotes the day-to-day temperature variability aggregated to that same 'green season'. $R_{r,y}$ refers to the total rainfall during the 'green season' of each year; $RM_{r,y}$ signifies the standardized monthly rainfall deviations; $R\hat{D}_{r,y}$ stands for the number of wet days, and $RD_{r,y}$ denotes the number of days with extreme rainfall.

Random effects μ_y and γ_r are introduced to capture unobservable factors that change over time and across regions, respectively. μ_y can account for global climatic and economic shocks that affect all regions simultaneously, such as evapotranspiration or global recessions. Besides, γ_r captures differences between regions, such as soil moisture content, which accounts for the impact of omitted variables. Generally, our econometric model attempts to control for $A_{r,y}$ through country and year random effects (γ_r and μ_y, respectively) and to model the regressions in different ways to represent the $M_{r,y}$ model (Ortiz-Bobea *et al* 2021). To reveals the differences between different economic level regions, we applied the same regression model to countries with different economic levels, and obtained different regression results.

The partial derivative of the independent variable is used to express the marginal effect of an independent variable, which represents the percentage change in the growth rate of agricultural TFP (For details see SI 1.6) for an increase of one unit in the independent variable. Specifically, the marginal effect of $\bar{T}_{r,y}$ is denoted as $ME_{\bar{T}_{r,y}} = \alpha_1 + 2\alpha_2 \bar{T}_{r,y} + \alpha_4 \tilde{T}_{r,y}$. This indicates that with a per unit increase in the monthly average temperature, TFP will change by $100^* ME_{\bar{T}_{r,y}}$%.

3. Results

Figure 2 depicts the temporal-spatial changes in agricultural TFP. As shown in figure 2(a), the average agricultural TFP has been increasing since 1961. The global growth rate of agricultural TFP has remained steady over the last fifty years (figure 2(b)). However, there is a significant spatial heterogeneity in the TFP growth rates, with Sub-Saharan Africa exhibiting low growth rates, while Brazil, Kazakhstan, China, the United States, and India show higher growth rates (figure 2(b)).

The regression results demonstrate that agricultural productivity is influenced by the higher-order moments of temperature and rainfall as well as their interactions. Notably, the interaction between average temperature, day-to-day temperature variability, and the number of wet days exerts a significant effect on crop yields. (see table 1). In the regression

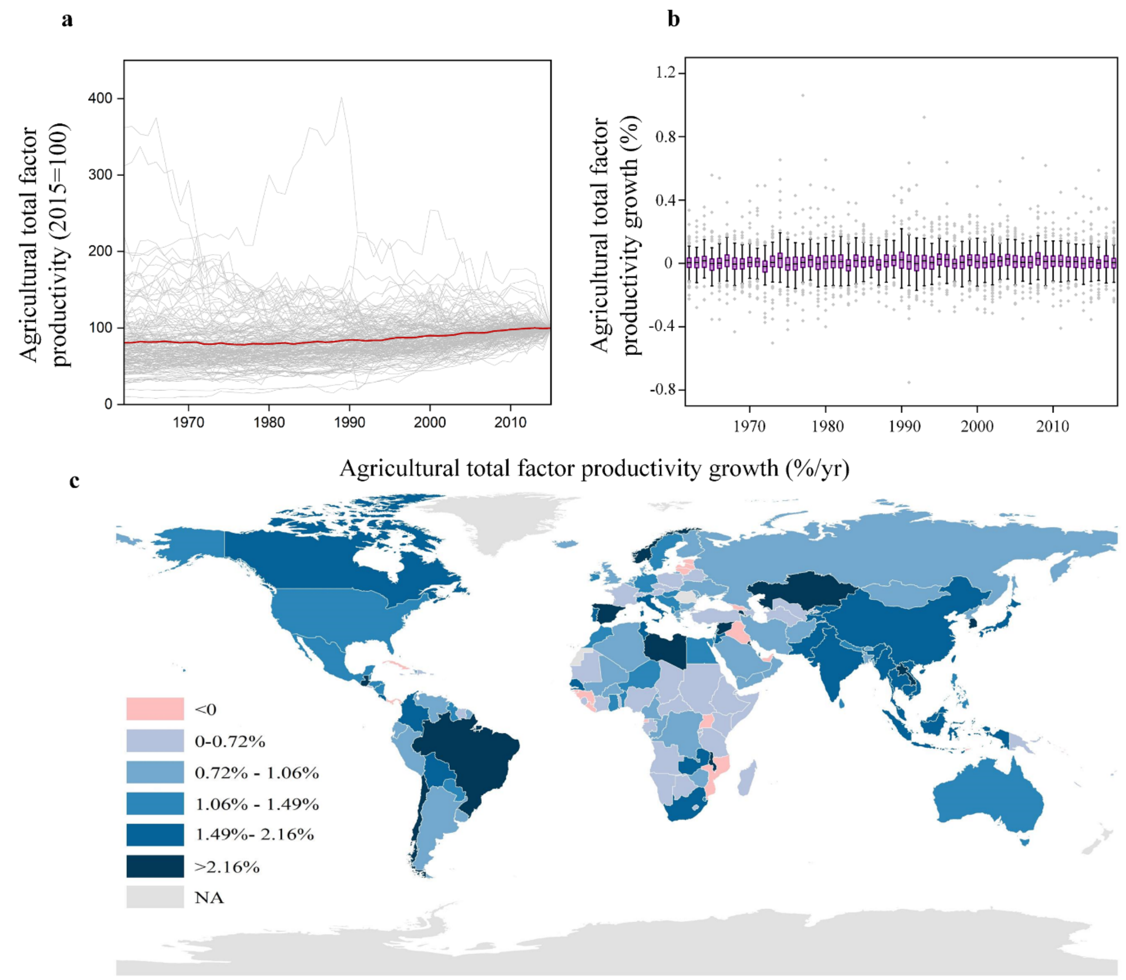

Figure 2. Trends and distribution in agricultural productivity. (a) Temporal trend in country-level agricultural TFP over 1961–2015, and red line represents the average agricultural TFP; (b) temporal trend in agricultural TFP growth rate over 1961–2015; (c) spatial distribution of agricultural TFP growth.

models, after incorporating various climatic measures, the influence of monthly average temperature, day-to-day temperature variability, and their interaction remains significant and consistent (see table 1, columns (1)–(3), columns (4)–(5), and columns (6)–(7), rows 1–4). This suggests that monthly average temperature and day-to-day temperature variability exert independent effects. Based on the adjusted R^2 and the BIC, the model presented in column (2) of table 1 is selected as the preferred specification. This setting and the results are also used when plotting the marginal effects of the various variables.

3.1. Effect of day-to-day temperature variability

Day-to-day temperature variability affects agricultural TFP in both direct and moderating ways. The direct effect of day-to-day temperature variability on agricultural TFP is negative, which means that higher variability tends to reduce the agricultural productivity. One unit increase of day-to-day temperature variability leads to a 2% decrease in TFP. However, day-to-day temperature variability also acts as a modulator. It can affect agricultural TFP by moderating the impacts of the monthly average temperature and the number of wet days (see table 1, columns (2), rows 4, 5, 16).

Day-to-day temperature variability influences agricultural TFP through its interaction with monthly average temperature. Our findings suggest that higher day-to-day temperature variability can mitigate the negative marginal effects of increasing monthly average temperature on agricultural TFP. Figure 3(a) illustrates that an increase in monthly average temperature generally leads to a decline in agricultural productivity when the marginal impact of temperature on TFP is below zero. However, higher day-to-day temperature variability moderates the rate of this decline. The red line in figure 3(a) represents a scenario with high day-to-day temperature variability (a value of 5), while the black line depicts a setting with low variability (a value of 0.5). A comparison of these lines demonstrates that regions with greater day-to-day temperature variability show smaller marginal effects on agricultural TFP as monthly temperatures

Table 1. Regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	5.324***	5.274***	5.3698***	5.28***	5.367***	5.291***	5.346***
$\bar{T}_{r,y}$	−0.09877***	−0.09643***	−0.1043***	−0.101***	−0.1079***	−0.1039***	−0.1068***
$\bar{T}_{r,y}*\bar{T}_{r,y}$	0.002597***	0.002546***	0.002712***	0.002649***	0.002793***	0.002723***	0.002787***
$\tilde{T}_{r,y}$	−0.03159**	−0.02053*	−0.05245***	−0.01702’	−0.04844***	−0.0141	−0.02584*
$\bar{T}_{r,y}*\tilde{T}_{r,y}$	0.00275***	0.002421***	0.003479***	0.002192***	0.003246***	0.002087***	0.002447***
$r_{r,y}$	0.0001726‘	0.0004653***	−0.00005529	0.0005074***	−0.00001509	0.0005503	0.0002413**
$r_{r,y}*r_{r,y}$	−0.0000001135	−0.000000287***	−0.00000002016	−0.0000003245***	−0.00000006699	−0.0000003547***	−0.0000001723*
$r\mathrm{M}_{r,y}$	0.04811***	0.04885***	0.04238***	0.03015**	0.02602*	0.02739**	0.02453*
$RD(99\%)_{r,y}$				−0.01497***	−0.01551***		
$RD(99.9\%)_{r,y}$						−0.08784***	−0.0755***
$RD(95\%)_{r,y}$	−0.008705***	−0.008801***	−0.008417***				
$RD(0.1\mathrm{mm})_{r,y}$	−0.002039***						−0.002025***
$RD(1\mathrm{mm})_{r,y}$		−0.003792***		−0.003841***		−0.003941***	
$RD(90\mathrm{mm})_{r,y}$			0.1363**		0.1668**		
$\tilde{T}_{r,y}*RD(0.1\mathrm{mm})_{r,y}$	−0.000191’						−0.0001928’
$\tilde{T}_{r,y}*RD(1\mathrm{mm})_{r,y}$		−0.0004672***		−0.0004514***		−0.0004688***	
$\tilde{T}_{r,y}*RD(90\mathrm{mm})_{r,y}$			−0.01191		−0.01581		
country_re	yes	yes	yes	yes	yes	yes	yes
year_re	yes	yes	yes	yes	yes	yes	yes
N	8575	8575	8575	8575	8575	8575	8575
adj R^2	0.2089531	0.213507	0.2060955	0.2093679	0.2024465	0.2098606	0.2118412
BIC	4844.352	4801.058	4846.635	4843.961	4883.265	4836.003	4822.856

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ‘$p < 0.1$

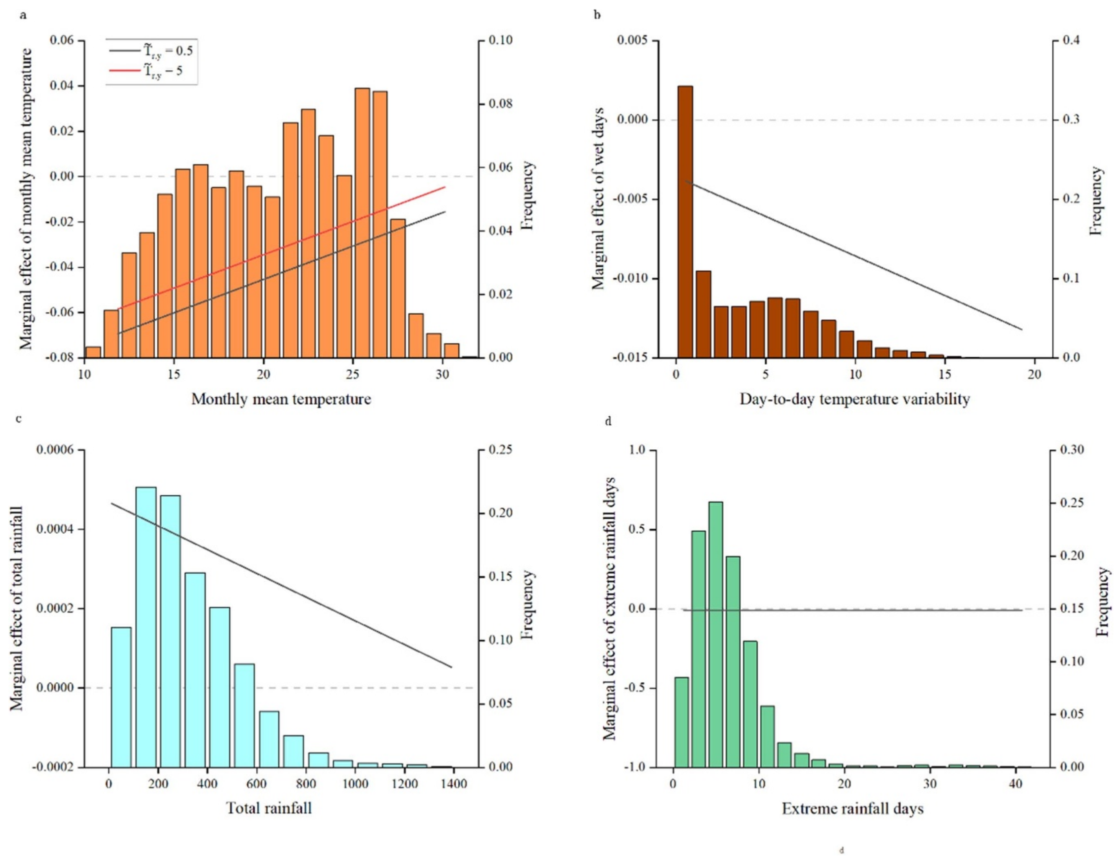

Figure 3. The marginal effect of four climatic metrics on agricultural growth. (a) The marginal effects of a 1-unit increase in monthly mean temperature. Red line is a function of the monthly mean temperature at day-to-day temperature variability $\tilde{T}_{r,y} = 5$, and black line is a function of the monthly mean temperature at day-to-day temperature variability $\tilde{T}_{r,y} = 0.5$ ($ME_{\bar{T}_{r,y}} = \alpha_1 + 2\alpha_2\bar{T}_{r,y} + \alpha_4\tilde{T}_{r,y}$). (b) The marginal effects of a 1-unit increase in wet days, and the corresponding line is a function of the day-to-day temperature variability ($ME_{R\hat{D}_{r,y}} = \alpha_8 + \alpha_{10}\tilde{T}_{r,y}$). (c) The marginal effects of a 1-unit increase in total rainfall, and the corresponding line is a function of the total rainfall ($ME_{R_{r,y}} = \alpha_5 + \alpha_6 R_{r,y}$). (d) The marginal effects of a 1-unit increase in extreme rainfall days, and the corresponding line is a function of the extreme rainfall days ($ME_{RD_{r,y}} = \alpha_9$). Histograms show the distribution of data for X-axis variables.

increase. In figure 4(a), we observe that areas like Central and Southern Africa, Central Asia, Eastern Europe, and Russia experience higher day-to-day temperature variability during their 'green season'. In contrast, regions such as South America, China, and Australia have lower variability during the same period. As shown in figures 4(b) and (c), regions with greater day-to-day temperature variability exhibit a lesser negative marginal impact of monthly average temperatures on agricultural TFP, which is observed in Central and Southern Africa and Central Asia.

Similarly, day-to-day temperature changes exacerbate the marginal effect of wet days on agricultural productivity. As depicted by the black line in figure 3(b), the curve is below zero, indicating that an increase in wet days results in a decrease in agricultural productivity. It is important to note that this decrease accelerates, highlighting that the negative impact becomes more evident as the number of wet days increases. Contrary to the moderating effect of monthly average temperatures on agricultural productivity, regions with higher day-to-day temperature variability experience a faster decline in TFP. Specifically, as day-to-day temperature variability increases, it amplifies the marginal impact of wet days on agricultural TFP. Figure 4(d) shows regions with a deeper purple hue, indicating a significant marginal impact of wet days on agricultural TFP. These regions correspond to the areas in figure 4(a) with high day-to-day temperature variability, such as central and southern Africa, Central Asia, Eastern Europe, and Russia.

3.2. Effect of the change of rainfall patterns

Agricultural TFP is influenced not only by temperature metrics but also by rainfall metrics, such as total rainfall and the number of extreme rainfall days (figure 3(c)). The impact of extreme rainfall on agricultural TFP is consistently negative. Figure 3(d) clearly shows this with a black line indicating a decline in TFP as the number of wet days exceeding the 95th percentile increases. Specifically, each additional day

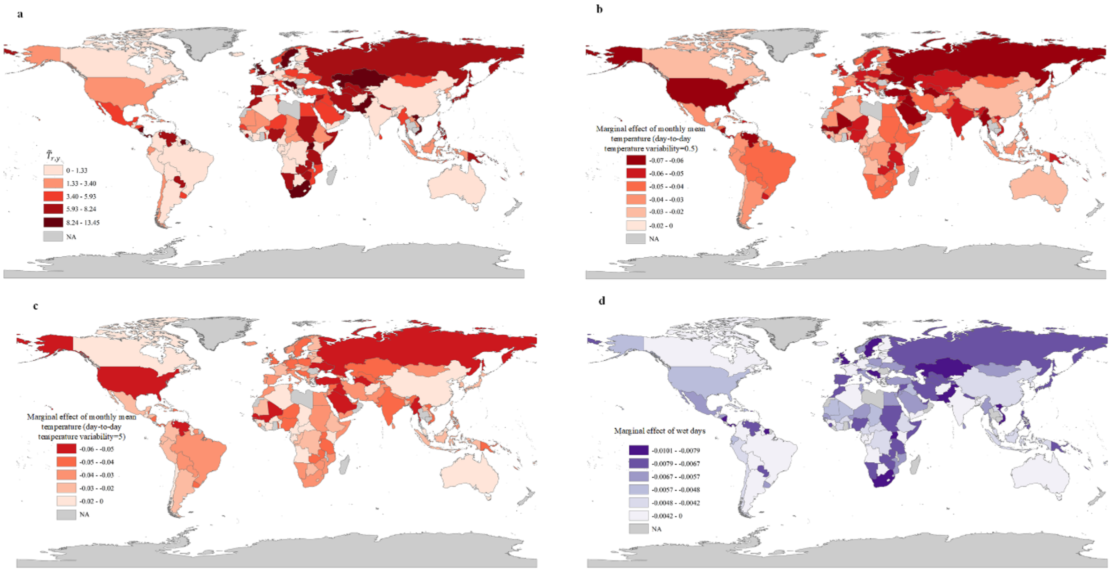

Figure 4. Day-to-day temperature variability distribution and national estimates of the marginal effect on agricultural productivity of a 1-unit shock of climatic variables. (a) Day-to-day temperature variability varies geographically. (b) The global marginal effect of monthly mean temperature at $\tilde{T}_{r,y} = 5$. (c) The global marginal effect of monthly mean temperature at $\tilde{T}_{r,y} = 0.5$. (d) The global marginal effect of wet days.

of extreme rainfall leads to a 0.88% reduction in agricultural TFP. Furthermore, our comparative analysis shows a direct correlation between extreme rainfall intensity and its negative impact on agricultural productivity. This correlation is particularly evident in table 1, columns (2), (4), and (6), where an increase in the number of wet days above the 99th percentile results in a more significant decline in TFP. In these circumstances, each additional day of extreme rainfall results in a 1.5% reduction in agricultural TFP.

3.3. Heterogeneity of the effect considering income levels

We built two models in high-income countries and low-income countries separately. In low- and lower-income regions, the impacts of both average temperature and day-to-day temperature variability on agricultural productivity are more evident compared to high-income regions (table 2 and supplementary figure 3). This could be attributed to the more frequent occurrence of high average temperatures and higher day-to-day temperature variability in these regions (see supplementary figure 4). Additionally, these regions typically are less resilient to extreme heat and temperature variability, which makes them more vulnerable to climate change (Dell *et al* 2012). Furthermore, the modulating effect of day-to-day temperature variability on the marginal impact of wet days is also significant in these lower-income regions. These regions are also affected by the total rainfall and the number of extreme rainfall days, with the influence being more pronounced than in high-income regions.

Table 2 shows that in high-income regions, overall rainfall and extreme rainfall have no significant impact on agricultural productivity. This is likely due to the advanced technologies and infrastructure in these wealthier nations, which enable farmers to deal with the effects of rainfall more efficiently (Dell *et al* 2012). Among rainfall-related metrics, only rainfall deviation has a significant influence on agriculture (table 2).

4. Discussion and conclusions

This study investigated the impact of day-to-day temperature variability, rainfall, and extreme rainfall on agricultural productivity at a national scale across the globe for 1961–2018. We lay particular emphasis on the role of day-to-day temperature variability on agricultural productivity and highlight the heterogeneity in its impact across countries with varying income levels.

In contrast to previous literature on the impact of climate change on agriculture, which primarily focused on the effects of annual temperature variability on crop yield (Wheeler *et al* 2000, Bhatt *et al* 2019, Rafique *et al* 2023) or agricultural productivity (Gornall *et al* 2010, Rahman and Anik 2020, Donadelli *et al* 2022), this study investigated the influence of day-to-day temperature variability. We found that this form of variability not only exerts a direct negative impact on agricultural productivity but also modulates it through interactive effects with other variables. This is consistent with previous results on intra-seasonal temperature variability

Table 2. The heterogeneity of the effect of climatic variables by income. Coefficients from two regression models are shown. Standard errors are shown in parentheses. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $'p < 0.1$.

	Low- and lower-income countries	High-income countries
Intercept	6.67^{***}	5.14^{***}
	(0.15)	(0.25)
$\bar{T}_{r,y}$	-0.25^{***}	-0.09^{***}
	(1.50×10^{-2})	(2.51×10^{-2})
$\bar{T}_{r,y} * \bar{T}_{r,y}$	$6.28 \times 10^{-3***}$	$2.39 \times 10^{-3***}$
	(3.74×10^{-4})	(6.35×10^{-4})
$\tilde{T}_{r,y}$	-0.14^{***}	$-0.04'$
	(1.26×10^{-2})	(2.25×10^{-2})
$\bar{T}_{r,y} * \tilde{T}_{r,y}$	$8.34 \times 10^{-3***}$	$3.24 \times 10^{-3**}$
	(6.41×10^{-4})	(1.05×10^{-3})
$R_{r,y}$	$9.12 \times 10^{-4***}$	-1.66×10^{-4}
	(1.35×10^{-4})	(2.56×10^{-4})
$R_{r,y} * R_{r,y}$	$-5.73 \times 10^{-7***}$	9.74×10^{-8}
	(9.35×10^{-8})	(1.73×10^{-7})
$RM_{r,y}$	-7.64×10^{-3}	$7.62 \times 10^{-2**}$
	(1.40×10^{-2})	(2.72×10^{-2})
$RD(95\%)_{r,y}$	-0.01^{***}	-7.75×10^{-3}
	(2.35×10^{-3})	(4.75×10^{-3})
$RD(1\text{mm})_{r,y}$	-1.26×10^{-3}	-2.35×10^{-3}
	(8.85×10^{-4})	(1.43×10^{-3})
$\tilde{T}_{r,y} * RD(1\text{mm})_{r,y}$	$2.82 \times 10^{-4*}$	6.52×10^{-5}
	(1.33×10^{-4})	(2.55×10^{-4})
country_re	yes	yes
year_re	yes	yes
N	3844	2394
adj R^2	0.54	0.56
BIC	−372.69	1083.10

affecting crop yields in the southeastern United States (Eck *et al* 2020). However, existing literature has not yet explored the modulating effects of day-to-day temperature variability on other influencing factors to agricultural productivity. This study concluded that day-to-day temperature variability can mitigate the marginal negative impact of monthly average temperature on TFP. High average temperatures with fluctuations allow for cooler days that benefit crop growth, while low average temperatures with warmer days can also support growth (Yang *et al* 2017). This offset may be due to increased farmer awareness of climate variability, enabling adaptive strategies (Abid *et al* 2019), such as improved irrigation and temperature regulation techniques (Rapholo and Diko Makia 2020). Additionally, this study also revealed that day-to-day temperature variability exacerbates the negative marginal effects of wet days on TFP. Day-to-day temperature variability and regional rainfall patterns have a bi-directional effect, thus adversely affecting crop yields. Increased temperatures can evaporate soil moisture (Seneviratne *et al* 2010, Lesk *et al* 2021), and increasing water vapor in the air. When there is a drop of temperature, this water vapor condenses into rain (Lenderink *et al* 2010, Ali *et al* 2018) and leads to increased rainfall. This phenomenon may be attributed to an increase in rainfall, which has led to an elevated rate of empty shells in the crop (Potopová *et al* 2017, Davis *et al* 2019).

Beyond temperature-related factors, rainfall metrics, such as total rainfall and the number of extreme rainfall days, also impact on agricultural productivity (Amare *et al* 2018). This study demonstrates a diminishing positive marginal effect of total rainfall on agricultural productivity, which shifts to a negative impact as rainfall levels continue to rise. Excessive rainfall can also lead to the exposure of pollutants in agricultural and pasture soils. This not only potentially causes damage to crops but also affects the quality of fodder, thereby dampening livestock production (Godde *et al* 2021). This analysis further substantiated that the number of extreme rainfall days exerts a consistent negative marginal effect on agricultural productivity. Similarly, this negative impact is related to not only crop yields (Troy *et al* 2015) but also livestock production (Habte *et al* 2022). This study suggests that the severity of extreme rainfall events amplifies their harmful effects, particularly during crop germination and maturation stages. For instance, in rice production, extreme rainfall affects the number of filled grains and effective panicles, with the impact closely tied to rainfall intensity (Fu *et al* 2023).

The effects of temperature, rainfall, and their interactions on agricultural productivity vary significantly among countries with differing income levels. This study found that in low-income regions, both temperature and rainfall significantly impact agricultural productivity (Di Falco *et al* 2012). In contrast, in high-income countries, while temperature exerts an evident influence, the role of rainfall is less significant, which also agrees with the finding of a previous study (Doğanlar *et al* 2022) that specifically focuses on the effects of climate change on the total economic output in high-income regions. Comparing the impact of temperature and rainfall on TFP between high-income and low-income countries, we find that the regression coefficients for most low-income countries are higher than those for high-income countries. This discrepancy can be attributed to several factors. High-income countries implement climate-smart measures, such as agricultural sensors, enhancing food production (Gangwal *et al* 2019). In contrast, low-income countries often lack these measures and struggle to adjust to weather changes, making their TFP more sensitive to temperature and rainfall variations. Additionally, low-income countries commonly practice monoculture, leading to soil nutrient depletion, degraded soil health, increased pest infestations, and reduced insect diversity (Maja *et al* 2021). Long-term monoculture hinders adaptation to climate change (Feliciano 2019), exacerbating TFP sensitivity in low-income countries. Therefore, these findings emphasize the need to adapt policy measures to region-specific conditions and vulnerabilities when designing and implementing climate change adaptation strategies.

There are some limitations and directions for future research. First, since TFP only has access to national-scale data, the global results we get may mask disparities between regions. This makes it important to produce a regional-scale TFP datasets in the future. Second, there might be some uncertainties in the simulated (reanalyzed) rainfall for low-income countries in the results of global and regional rainfall simulations. For example, W5E5 has lower interannual variability than ERA5 for regions such as Timor Leste (For details see SI 1.7). This highlights the need for improvement in future studies. This study provides essential support that can enable farmers worldwide to better adapt to climate change and extreme weather conditions.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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ORCID iDs

Zhixiao Zou https://orcid.org/0000-0001-9733-1276
Chaohui Li https://orcid.org/0000-0002-3951-7141
Xudong Wu https://orcid.org/0000-0002-0752-0282
Changxiu Cheng https://orcid.org/0000-0003-2988-8915

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